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# Epidemiological changes of scarlet fever before, during and after the COVID-19 pandemic in Chongqing, China: a 19-year surveillance and prediction study

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## Abstract

**Background** This study aimed to investigate the epidemiological changes in scarlet fever before, during and after the COVID-19 pandemic (2005–2023) and predict the incidence of the disease in 2024 and 2025 in Chongqing Municipality, Southwest China.

**Methods** Descriptive analysis was used to summarize the characteristics of the scarlet fever epidemic. Spatial autocorrelation analysis was utilized to explore the distribution pattern of the disease, and the seasonal autoregressive integrated moving average (SARIMA) model was constructed to predict its incidence in 2024 and 2025.

**Results** Between 2005 and 2023, 9,593 scarlet fever cases were reported in Chongqing, which resulted in an annual average incidence of 1.6694 per 100,000 people. Children aged 3–7 were the primary victims of this disease, with the highest average incidence found among children aged 6 (5.0002 per 100,000 people). Kindergarten children were the dominant infected population, accounting for as much as 54.32% of cases, followed by students (34.09%). The incidence for the male was 1.51 times greater than that for the female. The monthly distribution of the incidence showed a bimodal pattern, with one peak occurring between April and June and another in November or December. The spatial autocorrelation analysis revealed that scarlet fever cases were markedly clustered; the areas with higher incidence were mainly concentrated in Chongqing's urban areas and its adjacent districts, and gradually spreading to remote areas after 2020. The incidence of scarlet fever increased by 106.54% and 39.33% in the post-upsurge period (2015–2019) and the dynamic zero-COVID period (2020–2022), respectively, compared to the pre-upsurge period (2005–2014) ($P < 0.001$). During the dynamic zero-COVID period, the incidence of scarlet fever decreased by 68.61%,

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25.66%, and 10.59% ($P < 0.001$) in 2020, 2021, and 2022, respectively, compared to the predicted incidence. In 2023, after the dynamic zero-COVID period, the reported cases decreased to 1.5168 per 100,000 people unexpectedly instead of increasing. The cases of scarlet fever are predicted to increase in 2024 (675 cases) and 2025 (705 cases).

**Conclusions** Children aged 3–7 years are the most affected population, particularly males, and kindergartens and primary schools serving as transmission hotspots. It is predicted that the high incidence of scarlet fever in Chongqing will persist in 2024 and 2025, and the outer districts (counties) beyond urban zone would bear the brunt of the impact. Therefore, imminent public health planning and resource allocation should be focused within those areas.

**Keywords** Scarlet fever, COVID-19, SARIMA model, Epidemiology

## Introduction

Scarlet fever, caused by *Streptococcus pyogenes* (a group A streptococcus; GAS) used to be one of the most common acute respiratory seasonal infections, which mostly occurred in children under the age of 10 [1, 2]. The disease is mainly transmitted via air droplets (e.g., saliva or nasal discharge), close contact with the mucus or the skin of an infected patient, and fomites [3]. Its clinical features are high fever, headaches, sore throat, swollen lymph nodes, sandpaper-like red rash, and peeling and desquamation after the rash [4].

Scarlet fever used to be a common infectious disease among children, especially in Europe during the 18th and 19th centuries [1, 5]. The development of effective treatments (e.g., antibiotics) and the improvement of living standards (e.g., hygiene and nutrition) led to the disappearance of scarlet fever as a major cause of death in the worldwide pediatric population by the mid-20th century [6, 7]. However, in the 21st century, the disease has reemerged in some areas, as evidenced by outbreaks in several Asian countries and regions, including Vietnam (2009) [1], mainland China and Chinese Hong Kong (2011) [8, 9], and South Korea (2015) [10]. The incidence of scarlet fever has shown a dramatic upward trend in some European countries, such as Poland (2013) [11], the United Kingdom (2014) [12], and Germany (2007–2016) [13].

In 1950, scarlet fever was classified as a category B notifiable infectious disease in China. In the early 1980s, it caused serious public health problems and a considerable economic burden, after which the incidence gradually decreased [14]. Since the National Expanded Program of Immunization was launched in 2008, the incidence of vaccine-preventable infectious diseases among children in China has declined [15]. In contrast, cases of scarlet fever, for which there is no vaccine, have shown a substantial increase in the past 19 years in the country [16]. The annual average incidence went from 1.46 cases per 100,000 people in 2004 to 4.76 cases in 2011, peaking in 2018 at 5.68 cases [17]. The incidence remained high until the outbreak of COVID-19 at the end of 2019 [18]. Several studies have found dramatic reductions in the incidence of multiple respiratory infections, such as scarlet fever, seasonal influenza, and mumps, after the beginning of the pandemic in China [19, 20].

Scarlet fever is one of the main respiratory infectious diseases in Chongqing Municipality. According to our surveillance, the incidence of scarlet fever in Chongqing ranked 23th among Chinese Mainland (including 31 provinces, municipalities and autonomous regions) in 2019, 9th in 2022 and 22nd in 2023. Over the past 19 years, the incidence of scarlet fever cases in Chongqing has fluctuated, with a relatively high level in recent years, while the COVID-19 prevention and control has had an impact on the disease, leading to some changes in its epidemiological characteristics. However, scarlet fever was neglected and no studies have been conducted on these changes before, during and after the COVID-19 pandemic and on how the disease will evolve after COVID-19 pandemic in the Municipality. Thus, we investigate the epidemiological changes of scarlet fever before, during and after the COVID-19 pandemic (2005–2023) and predict the cases of the disease in 2024 and 2025 after the end of the dynamic zero-COVID strategy in Chongqing Municipality, Southwest China.

## Methods

### Study area

Chongqing situated in Southwest China (north latitude 28°10'~32°13', east longitude 105°11'~110°11') and has a moist monsoon climate typical of semitropical zones. It is one of the regional economic centers and the largest province-level Municipality under direct control of the national government (82,402.95 square kilometers). It is composed of 26 districts, eight counties, and four autonomous counties. At the end of 2023, the permanent resident population amounted to 31.914 million people.

### Case definitions and data sources

In response to the severe acute respiratory syndrome outbreak of 2003, the Chinese government established a real-time National Notifiable Infectious Disease Surveillance System (NNIDSS) for 41 infectious illnesses. Based on their severity, these illnesses are divided into three categories (A, B, and C), which must be reported according to a specified time frame. Scarlet fever is classified as a category B notifiable infectious disease, and all suspected, clinically diagnosed, and laboratory-confirmed cases must be reported to the NNIDSS within 24 h of detection, according to the 2004 Chinese Infectious Diseases Law. The centers for disease control and prevention supervise and inspect the reporting of infectious diseases every year to ensure that every diagnosed infectious disease including scarlet fever is reported. The definitions for suspected, clinically diagnosed and laboratory-confirmed cases of scarlet fever should comply with the diagnosis of WS 282–2008 issued by the Ministry of Health of the People's Republic of China (see Supplementary Material 1).

#### Data collection

In this observational study, data was collected from NNIDSS for all scarlet fever cases residing in Chongqing, encompassing suspected, clinically diagnosed, and laboratory-confirmed cases. All identifiable patient personal information was anonymous in this study. The data included age, gender, address, date of symptom onset, case classification, clinical diagnosis and laboratory test outcome, and it covered the period from January 1, 2005, to December 31, 2023.

The resident population data for Chongqing from 2005 to 2023 was downloaded from the official website of the Chongqing Statistical Yearbook (http://tjj.cq.gov.cn/zwgk_233/tjnj/) and was updated at the end of every year. The birth rate data was sourced from China's official *Statistical Yearbook*. "Prenursery children" are children aged 0–2 who are taken care of by family members and/or a nanny at home. "Kindergarten" is a form of education for children aged 3–6. "Students" refers to individuals aged over 7 who are studying (from primary school to college). The winter holidays and summer holidays for primary and secondary schools were based on information released by the Chongqing Municipal Education Commission. Overall, the winter holiday starts from mid-January to late February, and the summer holiday is from early July to the end of August every year.

#### Statistical analysis

The incidence of scarlet fever (per 100,000 people) was defined as the number of cases per year divided by the population size. A two-proportion Z-test was used to evaluate whether the annual incidence change between two proportions was statistically significant based on the assumption that the groups were independent of each other [21]. The basic steps included collecting the annual average incidence data of scarlet fever in Chongqing at different stages of the research, calculating the proportion, calculating the *Z* value, determining the significance level, making statistical inference and interpreting the results. Two-proportion Z-test was performed using R 4.3 (Vienna, Austria). A p-value $\leq 0.05$ was considered statistically significant.

The annual incidence of scarlet fever in Chongqing was visually presented on a district (county)-level map utilizing various hues, where darker shades signify higher rates of incidence. Utilizing ArcGIS 10.8 (ArcMap, ESRI Inc., Redlands, CA, USA), a spatial model was constructed to compare the average incidence of different regions in the same timeframes horizontally and the average incidence of different timeframes in the same region vertically, based on the public geographic data downloaded from the Resource and Environmental Science Data Platform, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (https://www.resdc.cn/). Spatial autocorrelation analysis was utilized to explore whether there was a correlation in the study region from a global perspective and to describe the spatial graph of the attribute values in said region [22]. The Moran's I value indicated whether there was clustering and the magnitude of clustering in the spatial distribution, with a value of [-1,1]. Moran's I value $>0$ indicates a positive spatial autocorrelation, and a larger value indicated a higher degree of spatial clustering. Moran's I value close to -1 indicates strong negative spatial autocorrelation. Moran's I value $=0$ indicates no spatial autocorrelation. Local spatial autocorrelation analysis used local indicators of spatial association (LISA) maps to detect whether a local region was one of the four clustering regions: high-high, high-low, low-high, and low-low. High-high and high-low were considered to have high incidence of scarlet fever in this region, while low-low spot was considered to have a lower incidence. The significance level of all these analyses was set at 0.05 in two-tailed tests.

In addition, R 4.3 (Vienna, Austria) was used to draw graphs, and Excel 2021 was used for data cleaning, sorting, preliminary analysis and plotting.

#### Establishment of the SARIMA model

Considering that the reported incidence of the scarlet fever dataset presented obvious periodicity and seasonality of the seasonal autoregressive integrated moving average (SARIMA) was conducted. This model can be generally expressed as SARIMA (p, d, q) $\times$ ($P$, $D$, $Q$)$_{[n]}$. In the process of forming this model, the seasonality of scarlet fever was considered as the explanatory variable and the monthly incidence of scarlet fever was the response variable. The parameters p, d, and q represent the orders of the nonseasonal autoregression, difference, and moving average, respectively; $P$, $D$, and $Q$ are the corresponding seasonal autoregression, seasonal differences in times, and moving average orders respectively. Finally, n denotes the seasonal periodicity of the sequence ($n=12$ in this study).

Building the SARIMA model followed these key steps: Firstly, Augmented Dickey-Fuller (ADF) method and seasonal decomposition were used to observe the stationarity and seasonality of the scarlet fever incidence series [23]. For the non-stationary series, differencing was adopted to maintain the stationarity of the series. Secondly, the autocorrelation function (ACF) graph and partial autocorrelation function (PACF) plots were selected to determine the order of model. The best SARIMA model was constructed by using the auto.arima function in the stats package of R 4.3 (Vienna, Austria). Thirdly, examine goodness of fit using the Akaike Information Criteria (AIC) and Bayesian information criterion (BIC) [24]. Fourthly, Ljung-Box Q test were adopted to assess whether the estimated residuals met the demand of a white-noise series [25]. Finally, to ensure a comprehensive and balanced evaluation, three indexes were employed to assess the performance of the model: the root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) [26].

## Results

### Incidence in different periods

From January 1, 2005, to December 31, 2023, a total of 9,593 scarlet fever sporadic cases were reported in Chongqing, which resulted in an annual average incidence of 1.6694 per 100,000 people. To evaluate the epidemiological features of scarlet fever and to visually demonstrate the impact of COVID-19 on the incidence of the disease, the study period was divided into timeframes: 2005–2019 (before-COVID-19 period), 2020–2022 (dynamic zero-COVID period) and 2023 (post dynamic zero-COVID period), while the before-COVID-19 period was further divided into 2 sub-periods: 2005–2014 (pre-upsurge period) and 2015–2019 (post-upsurge period), according to the time of re-emergence of scarlet fever in Chongqing.

The average annual incidence remained relatively stable and low in 2005–2010, with a slight increase after 2011 (1.634 per 100,000 people). The first upsurge in cases occurred in 2015, with a significantly higher incidence of 3.121 per 100,000 people; this rise continued and peaked in 2019 (3.018 per 100,000 people). This trend changed completely when the incidence dropped sharply in 2020 (0.854 per 100,000 people), while the situation was reversed in 2021–2022, and peaked in 2022 (2.3903 per 100,000 people), which then decreased in 2023 (1.5168 per 100,000 people). The annual incidence in 2023 was not only lower than the average level of dynamic zero-COVID period (1.6947 per 100,000 people), but also lower than the average (calculated across the whole period 2005–2023, 1.6694 per 100,000 people) (Fig. 1A). The incidence increased by 106.54% in the post-upsurge period (2015–2019) and by 39.33% during the dynamic zero-COVID period (2020–2022), compared to that in the pre-upsurge period (2005–2014) ($P<0.001$). The incidence decreased by 32.54% during the dynamic zero-COVID period (2020–2022) compared to that in the post-upsurge period (2015–2019) ($P<0.001$). The incidence increased by 10.50% in 2023 compared to that in the dynamic zero-COVID period (2020–2022) ($P<0.05$). (see Supplementary Material 2).

There was a bimodal seasonal pattern in the monthly incidence. The first peak usually occurred in late spring, mainly between April and June, about two or three months after the spring semester had begun, with the highest monthly incidence (5.2496 per 100,000 people) recorded in June. The second peak typically happened in November or December, about two or three months after the autumn semester had begun. The first peak was much higher than the second. Every year, the monthly incidences reached the two lowest levels during the school holidays in spring and summer (Fig. 1B).

### Epidemiological characteristics

Of the 9,593 cases, 5,751 were male and 3,842 were female, with a gender ratio of 1.5:1. Scarlet fever cases were detected in all age groups, however the median age at onset was 5 years (ranging from 3 days to 78 years), children aged 6 had the highest average annual incidence (5.0002 per 100,000 people) and those aged 60 or older had the lowest average annual incidence (0.0100 per 100,000 people). Kindergarten children were the dominant infected population, accounting for as much as 54.32% of cases, followed by students (34.09%), prenursery children (9.77%), and others 1.82%.

The pattern of reported scarlet fever cases was analysed by the age and sex. In the total population, the average incidence was persistently higher among males than females. The cases were mainly distributed in the 3–7 age group in both males and females, accounting for an overwhelming 67.54% of total cases. The incidence of the 4-year-old, 5-year-old, and 6-year-old age groups fluctuated significantly in different years (Fig. 2A). The annual incidences peaked in different years among different age groups. The annual incidence of cases aged 0–2 years fluctuated relatively steadily, with the peak being reached in 2018. The annual incidence among cases aged 3–6 years peaked in 2015, 2018, 2019, and 2022, whereas for the 7–14 years, it peaked in 2015, 2019, and 2022. In contrast, the annual incidence among individuals over 14 years consistently remained notably lower in comparison to the other age groups (Fig. 2B).

### Spatial distribution

The spatial distribution of scarlet fever cases revealed that there were differences in the incidence in different regions during the four periods. The areas with higher

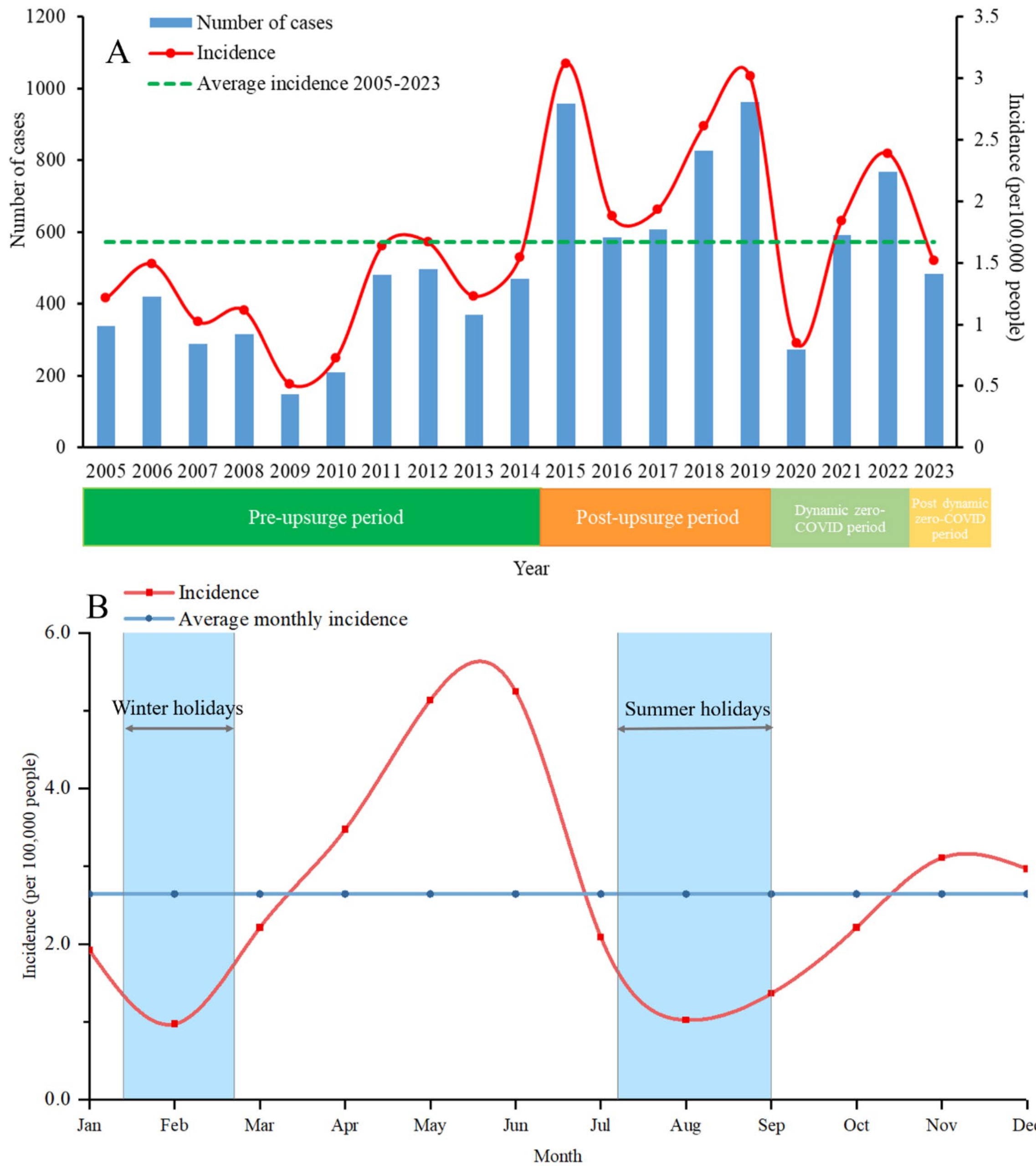


**Fig. 1** (**A**) Annual incidence of scarlet fever in Chongqing, 2005–2023. (**B**) Monthly incidence of scarlet fever (12-month period) in Chongqing. *Notes*: The blue areas indicate the school holidays in spring and summer

incidence were mainly Chongqing's urban zone and its nearby districts from 2005 to 2014 (Fig. 3A). From 2015 to 2019, although the incidence was still higher in the urban zone and the adjacent districts, the southeast of Chongqing, especially Qianjiang district, became a high endemic region (Fig. 3B). Since the beginning of 2020, the incidence of scarlet fever in the urban zone decreased, however, it had gradually spread to remote areas in the east and northwest of Chongqing (Fig. 3C and D).

The global autocorrelation results of scarlet fever in Chongqing could be found in Supplementary Material 3. The global Moran's I value ranged between 0 and 1, indicating the presence of some degree of spatial autocorrelation among the observed cases of scarlet fever during the study period. Statistically significant autocorrelation ($P<0.05$) during the Pre-upsurge and Post-upsurge periods indicated that there was a positive spatial correlation in the incidence of scarlet fever among the districts (counties) within those specific time frames. This meant that areas with higher or lower incidence of scarlet fever tend to cluster together spatially, which suggested that

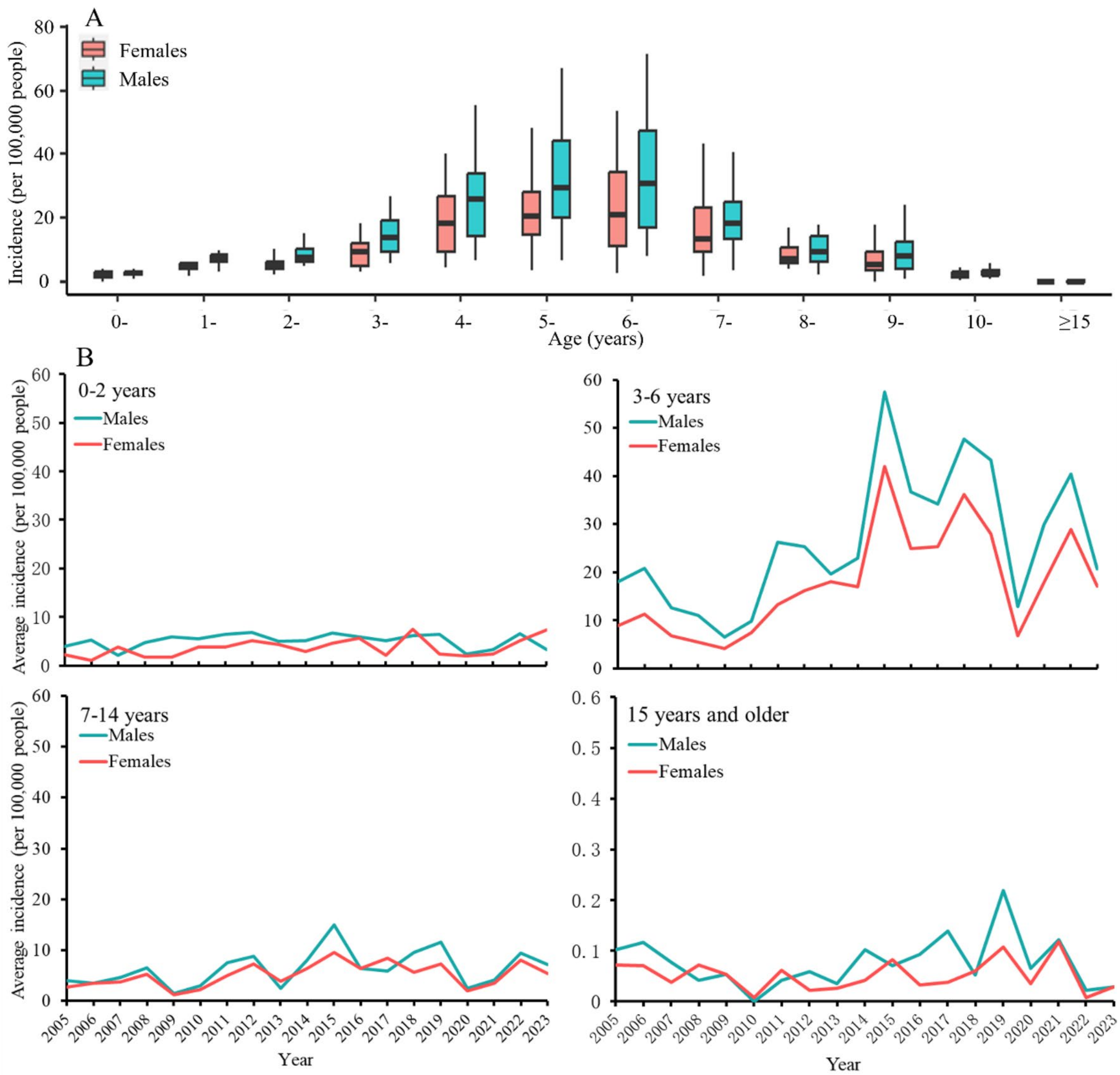


**Fig. 2** (**A**) Gender-specific distribution of reported scarlet fever cases by age in Chongqing, 2005–2023. (**B**) The annualized average incidence by age group and gender in Chongqing, 2005–2023

some underlying spatial factors may have influenced the distribution of scarlet fever cases during these periods.

Utilizing the district (county) level data of the average scarlet fever incidence in Chongqing from 2005 to 2023, a local spatial autocorrelation analysis was performed. The results of LISA clustering diagram indicated that there was an evident spatial correlation blinding the cases of scarlet fever diseases. The differences between the pre-upsurge period (2005–2014) and the post-upsurge period (2015–2019) were statistically significant ($P<0.05$), which revealed that the incidence had a significant positive spatial correlation at the county scale in the two stages in Chongqing and that the distribution of the cases was not random. The map for 2005–2014 showed that high-high cluster regions were mainly concentrated in Chongqing's urban zone and the adjacent Bishan district and Hechuan district (Fig. 3E); the incidence was also high in the surrounding regions. During the period from 2015 to 2019, apart from the high-high and low-high clusters observed in urban zone, Qianjiang district located in the southeast of Chongqing exhibited a noticeable high-low outlier. This outlier implied that the incidence in this region was comparatively high (Fig. 3F). Since 2020, the clustering trend in the urban zone of Chongqing has dissipated, whereas Youyang county in the southeast demonstrated a high-high cluster from 2020 to 2022, followed by a shift to a pattern of low surrounding areas surrounding high-incident zones in 2023 (Fig. 3G and H).

## Model establishment and prediction

Based on morbidity data from 2005 to 2019, the SARIMA model was used to predict the incidence of scarlet fever in 2020–2022, assuming no COVID-19 was present. Considering that there were obvious periodic characteristics,

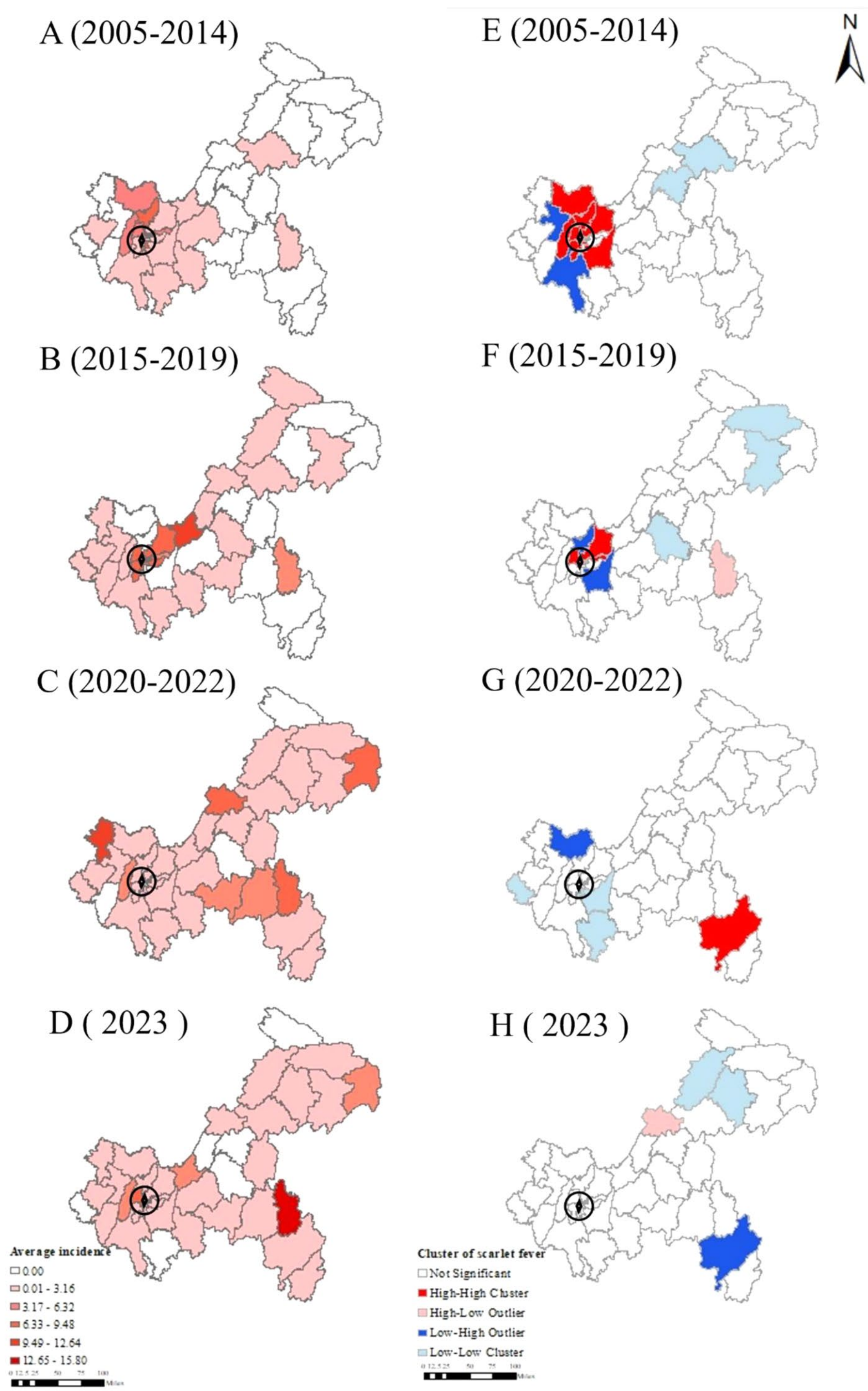


**Fig. 3** (**A–D**) Spatiotemporal distribution of annual average incidence of scarlet fever in Chongqing, 2005–2023. (**E–H**) Results of the local spatial autocorrelation analysis of incidence of scarlet fever in Chongqing, 2005–2023. The marked location in Fig. 3 is the urban zone of Chongqing

a one-step order difference (d=1) and a one-step seasonal difference ($D$=1) with a period of 12 seasonal differences were performed to eliminate the trends and seasonal effects, respectively. The final ADF supported that the data was a stationary time series ($P$<0.01). The ACF and PACF graphs had tail characteristics, given that the values of p, q, $P$, and $Q$ do not generally exceed 2; hence, trial orders from 0 to 2 were performed (see Supplementary Material 4). Based on the results of the goodness-of-fit test statistics, we confirmed the optimal SARIMA (1,0,0) (2,1,2) $_{[12]}$ model, with the minimum Akaike information criterion (AIC=1321.7382) and Bayesian information criterion (BIC=1330.6831) being the best. Finally, the results of the Ljung-Box Q test for the model showed that the residual sequence was a white noise series ($\chi^2$=0.0372, $P$=0.09). Additionally, the performances of the model were tested in terms of both simulation and prediction, and the results showed that the RMSE (15.05), MAE (10.99) and MAPE (39.92%) of the SARIMA (1,0,0) (2,1,2) $_{[12]}$ model were all relatively low. The model prediction showed that the number of scarlet fever cases that were expected to occur in Chongqing in 2020, 2021 and 2022 were 873, 795 and 859 whereas the actual number of cases were 274, 591 and 768 respectively, with a total of 895 averted cases, showing an unprecedented decline (Fig. 4). In other words, the reported annual incidence of the disease decreased by 68.61%, 25.66%, and 10.59% in 2020, 2021, and 2022, respectively, compared to the predicted value ($P$<0.001, see Supplementary Material 6).

The same method was used to establish a SARIMA model to predict the number of cases per month over the next two years, based on the actual number of scarlet fever cases in the period 2015–2019, the predicted number for 2020–2022 and actual number for 2023. The original data showed that the scarlet fever time series was not smooth; one-step difference (d=1) and seasonal difference ($D$=1) were determined, and the final ADF test was statistically significant ($P$<0.05), making the series smooth. The ACF and PACF graphs (see Supplementary Material 5) were generated to help estimate the other parameters. SARIMA (1,0,0) (2,1,0) $_{[12]}$ model was found to the optimal model, which had the lowest Akaike information criterion (AIC=810.5582) and Bayesian information criterion (BIC=823.0399). Therefore, p, d, q=1, 0, 0 and $P$, $D$, $Q$=2, 1, 0, respectively. This optimal model also passed the Ljung–Box Q Test ($\chi^2$=0.2876, $P$=0.5918) and extracted sufficient information. Additionally, the performances of the model were tested in terms of both simulation and prediction, and the results showed that the three index values of RMSE (14.47), MAE (0.049) and MAPE (28.20%) of the SARIMA (1,0,0) (2,1,0) $_{[12]}$ model were all relatively low, indicating good performance. The final prediction model found that there should be 675 and 705 cases of scarlet fever in Chongqing in 2024 and 2025, respectively, representing an increase from historical baselines (505 cases). The two monthly peaks in both years should be in June (102 cases in 2024, 108 cases in 2025) and December (85 cases in 2024, 87 cases in 2025), which is much higher than the annual average of June (84 cases) and December (47 cases) in previous years (Fig. 4).

## Discussion

Using a 19-year surveillance dataset of scarlet fever, we characterized patterns of disease incidence over the years in Chongqing, a Municipality located in Southwest China. We found that the upsurge of scarlet fever in Chongqing started in 2015. The epidemic of scarlet fever in Chongqing had undergone four distinct stages: 2005–2014 (pre-upsurge period), 2015–2019 (post-upsurge period), 2020–2022 (dynamic zero-COVID period) and 2023 (post dynamic zero-COVID period). Our research distinctly shows the pattern of scarlet fever incidence over the years, including changes in spatial and seasonal distributions, incidence at a specific age, and predicted the incidence trend for the upcoming two years.

The patterns of scarlet fever incidence were similar, but not identical, to the trend throughout China and other regions [27, 28]. In contrast to the more than 10-fold increase in Chinese Hong Kong, the upward trend of scarlet fever in Chongqing was less pronounced over the same period in 2011 [29]. The rapid rise in Chongqing

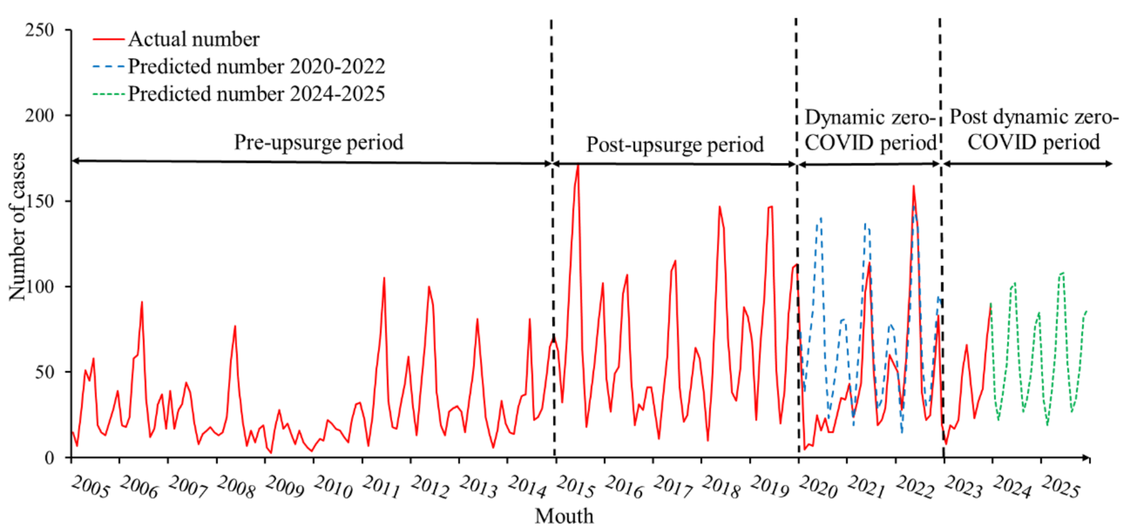


**Fig. 4** Prediction diagram of the monthly scarlet fever cases in the study period

seemed to begin in 2015 and peak in 2019, with the peak being four years later than that of overall national level [17]. Furthermore, we found that the highest incidence of the disease in Chongqing (3.121 per 100,000 people) was significantly lower than that in Beijing (14.25 per 100,000 people) during the 2005–2014 period [30], Shenyang (31.24 per 100,000 people) in 2018 [3], Chinese Hong Kong (18.1 per 100,000 people) in 2012–2015 [29] and South Korea (13.7 per 100,000 people) in 2015 [10]. During this period, the birth rate in Chongqing was lower than the national average, which resulted in a relatively low number of susceptible children [31]. The 2015 upsurge may have been affected by an increase in the number of cases nationwide and a higher risk of population exposure. Although 2020 witnessed a slight decline, the incidence rebounded in 2021 and 2022, which indicated that the influence of COVID-19 prevention and control measures on the elevated occurrence of scarlet fever was temporary and limited [32]. The incidence of scarlet fever decreased in 2023 unexpectedly, which might due to the heightened of public health awareness and more attention to disease prevention and control, such as wearing masks, keeping social distance, and washing hands frequently, shortly after COVID-19 pandemic in late 2022 and early 2023 [33].

Our study found that children aged 3–7 years, particularly males, were the group most affected by scarlet fever in Chongqing. The age profiling is consistent with evidence from other countries and regions [3, 12, 29, 34, 35]. This result could be partly attributable to the group's scarce immunity and the high risk of a concentrated population in kindergartens and primary schools, which might promote the spread of bacterial diseases [36]. In China, kindergarten education caters to children aged 3 to 6, whereas infants and toddlers within the 0–2 age bracket experience a notably lower risk of infection, attributed to their predominantly home-based environments. Males have a higher risk of infection than females, in all age groups, which might be due to stronger physical activities and poorer personal hygiene [34]. Remarkably, scarlet fever had a pattern with two annual seasonal peaks in Chongqing. The first peak typically occurred in April–June and the second one in November–December, which was consistent with the national trend [37] and directly related to students' school time. However, in 2020, this pattern was disrupted due to the implementation of measures to prevent and control the spread of COVID-19. Schools either suspended classes or offered them online, and even when schools reopened in 2020 in Chongqing, students were required to comply with strict public health rules [38]. In 2021–2022, scarlet fever incidence in Chongqing increased as COVID-19-related prevention and control policies were relaxed and face-to-face teaching resumed. This significant alteration in the scarlet fever trend during different context precisely indicates that scarlet fever is preventable, and the key time for prevention and control is before and during the two seasonal peaks, with kindergartens and primary schools being the key locations. As there is no scarlet fever vaccine currently, it is recommended that schools strengthen the implementation of public health interventions [39], such as morning and afternoon check systems, epidemic reporting system, isolation measures and patients home hygiene management, strengthened health education, and enhanced disinfection of public facilities and supplies. These measures contributed to a reduction in the spread of not only scarlet fever but also other infectious disease, including hand, foot, and mouth disease, rubella, pertussis, mumps and malaria [40].

The spatial distribution analysis demonstrated that before 2020, high-high cluster were mainly concentrated in Chongqing's urban zone and its adjacent districts with high population density, which proved that scarlet fever of Chongqing was not randomly distributed. This may suggest a potential link between the incidence of scarlet fever and the population density. Thereafter, the incidence of scarlet fever decreased in the urban zone while increased in the east and northwest of Chongqing in remote areas, especially in Youyang county, demonstrating a high-high cluster from 2020 to 2022. The reason could be partly attributed to the increasingly developed transportation in recent years, with more frequent personnel exchanges between the urban zone and remote areas. These results indicated that scarlet fever tends to cluster in urban zone with high population density and convenient transportation, which increases the risk of scarlet fever exposure [2, 3]. Prompting us that Chongqing should pay more attention to the prevention and control of scarlet fever in the outer districts (counties) beyond urban zone, strengthen monitoring and early warning, and invest more resources in these areas for prevention and control.

It is predicted that the high incidence of scarlet fever in Chongqing will persist in 2024 and 2025. It may even exceed the level seen before the COVID-19 pandemic. Upon spatial distribution analysis, it is evident that outer suburbs and counties beyond the urban zone would bear the brunt of the impact. Therefore, the disease might still be a major public health problem in Chongqing and the prevention and control of scarlet fever should be placed in a more prominent position in Chongqing and its surrounding areas. As scientific and reasonable epidemic-prevention measures could not only reduce the incidence of the diseases and protect public health but also promote the recovery and development of the economy [41], more resources should be allocated to areas outside the main urban region with a high incidence of scarlet fever. In the future, public health interventions, such as early vigilance, strengthening the monitoring of key high-risk groups and high-risk areas discussed above, and enhancing public health awareness, could prove effective in preventing and controlling the spread of scarlet fever in Chongqing and the rest of China.

## Conclusion

Over the past 19 years, scarlet fever has mainly threatened children aged 3–7 years, particularly males. Kindergartens and primary schools serving as transmission hotspots, and seasonal peaks are directly related to students' school time. Those revealed that Chongqing's prevention and control efforts should focus on these populations. It is predicted that the high incidence of scarlet fever in Chongqing will persist in 2024 and 2025, and spatially clusters concentrated in the east and northwest of Chongqing in remote areas. Therefore, imminent public health planning and resource allocation should be focused within those areas, especially in Youyang county. Early detection and prevention of high incidence areas will improve the efficiency of scarlet fever control and management in Chongqing.

### Abbreviations

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|---|---|
| COVID-19 | Coronavirus disease 2019 |
| SARIMA model | Seasonal autoregressive integrated moving average model |
| GAS | A group A streptococcus |
| NNIDSS | National Notifiable Infectious Disease Surveillance System |
| LISA map | Local indicators of spatial association map |
| ADF | Augmented Dickey-Fuller |
| ACF | Autocorrelation function |
| PACF | Partial autocorrelation function |
| AIC | Akaike information criteria |
| BIC | Bayesian information criterion |
| RMSE | Root mean square error |
| MAE | Mean absolute error |
| MAPE | Mean absolute percentage error |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-024-20116-5.

Supplementary Material 1

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### Author contributions

KS and YKC supervised the study. WGT and XNZ designed the study. TTL and QL collected and organized the data. TY and JS analyzed the data. LQ and JL interpreted the results. RW wrote the first draft. YX and JW reviewed and edited this manuscript. All the authors contributed to the final draft and approved the submitted version.

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### Data availability

The data that supports the findings of this study is available from the Chongqing CDC, but restrictions apply to its availability. The data was used under license for the current study, and it is not publicly available. However, the data is available from the authors upon reasonable request and with the permission of the Chongqing Center for Disease Control and Prevention. If anyone want to cooperate with Chongqing CDC and get data, please contact Chongqing CDC staff (E-mail: sukun325@163.com).

## Declarations

### Ethics approval and consent to participate

Our study was reviewed and approved by the Research Ethics Committee of the Chongqing Center for Disease Control and Prevention (reference number KY-2023-017-1).

### Consent for publication

Not applicable.

### Competing interests

The authors declare no competing interests.

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